

Discrepancies in the Spatial Assessment of Drought – the Vistula Catchment Study

Emilia KARAMUZ✉, Iwona KUPTTEL-MARKIEWICZ, Tesfaye SENBETA,

Ewa BOGDANOWICZ, and Jarosław J. NAPIÓRKOWSKI

Institute of Geophysics, Polish Academy of Sciences, Warsaw, Poland

✉ emikar@igf.edu.pl

Abstract

In the last decade, uncertainty in drought assessment studies has received increasing attention in the hydrometeorological research community. Spatio-temporal characteristics of drought are affected by uncertainties resulting from the calculation of standardized drought indices. To the best of our knowledge, no studies have been conducted so far on the impact of these uncertainties on the assessment of the spatial extent of droughts. In the present study, the uncertainty of determining the spatial extent of meteorological drought in individual classes is investigated for various probability distributions and the accumulation time scale used for determination of the Standardized Precipitation Index (SPI). In the studies, the E-OBS daily gridded precipitation data for the Vistula catchment in Poland were used along with four parametric distribution functions (Birnbaum-Saunders – BS, Weibull – WEI, Generalized Extreme Value – GEV, and Gamma – GAM) and nonparametric approach. Preliminary results indicate significant discrepancies in the spatial extent of individual drought category indicating higher uncertainty in determining the areas affected by severe and extreme droughts.

Keywords: drought, Standardized Precipitation Index, uncertainty analysis, probability distributions.

1. INTRODUCTION

The Standardized Precipitation Index (SPI) is one of the most widely used indicators in drought assessment studies due to its flexibility, spatial-temporal comparability, and quite simple calculation (McKee et al. 1993). Bearing in mind the above advantages, the World Meteorological Organization recommended SPI for meteorological drought assessment, pointing out that SPI allows for a reliable comparison of historical and current droughts between different climatic and geographic regions.

Nevertheless, the SPI is a relative measure. Its calculation depends mainly on the probability density function (PDF) adopted as well as on the method used for parameter estimation and the reference period used in the estimation (Wang et al. 2021). Nowadays, the drought research community focuses on some issues related with applying SPI in different regions. The most questionable is the selection of the adequate probability distribution to fit the cumulative precipitation, the proper time scale, the data length, and the adequacy of the assumption of non-stationarity of the observations.

The proper choice of probability distribution for precipitation is the basis for accurate SPI calculation. The use of different types of distributions lead to different SPI values and may introduce inaccuracies in the assessment of the extent of the impact of the drought phenomenon. In the present study, the uncertainty of meteorological drought extent determination in specific classes is investigated from a candidate probability distribution perspective and the cumulative time scale. The study's main goal was to compare and highlight the discrepancies in determining the spatial extent of drought impacts resulting from using different candidate distributions to calculate SPI.

2. MATERIALS AND METHODS

The SPI was determined for the catchment area of the Vistula River (194 000 km²), the largest river in Poland (Fig. 1a.). Studied basin is located mainly on the Polish territory and occupies 54% of the country. The study used Europe-wide E-OBS ensemble daily precipitation data set delivered by the European Climate Assessment & Dataset project (ECA&D). The gridded data set covers the period 1950–2020 and has spatial resolution at a spacing of $0.1^\circ \times 0.1^\circ$ in regular latitude/longitude coordinates. The spatial distribution of the long-term (1950–2020) average annual precipitation for the study area is shown in Fig. 1b. The highest yearly average precipitation totals are observed in the southern part of the catchment, where there are mountainous areas. In general, precipitation decreases from south to north, with a clearly distinguishable area of the lowest precipitation in the central part of the catchment.

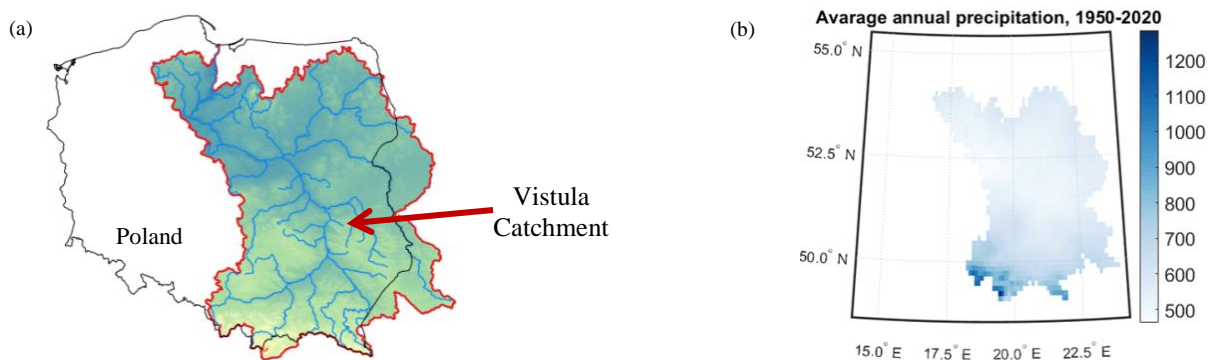


Fig. 1: (a) Study area and (b) spatial distribution of average annual precipitation (1950–2020).

The SPI is calculated as a transformation of one probability distribution (in this case, four probability distributions were used: BS, WEI, GEV, GAM) to the normal distribution using a long-term cumulative precipitation data at a given level of aggregation. Calculation of SPI was done for four aggregation scales, i.e., 1, 3, 6, and 12 months. The goodness-of-fit of the PDF for the E-OBS precipitation data was evaluated based on non-parametric Kolmogorov–Smirnov (KS) test and Akaike Information Criterion (AIC).

3. PRELIMINARY RESULTS

The four PDFs considered were tested for their goodness-of-fit to the precipitation data of different aggregation periods. Figure 2 shows the result of the KS test for the individual PDFs. The pixels highlighted in yellow indicate the regions where the null hypothesis regarding the fit of the proposed PDF cannot be accepted at a significance level of $\alpha = 0.005$, while catchment areas highlighted in dark blue meet the null hypothesis.

The results of the KS test for the GAM and GEV distributions satisfy the null hypothesis for all of the aggregation periods tested and for almost the whole catchment area. The worst performance is for the BS distribution for the 1-month accumulation period. The BS distribution performs comparable to the GEV and GAM distributions for other aggregation scales. The WEI distribution does not meet the null hypothesis for the 3, 6, and 12-monthly accumulation periods for most of the catchment area, and this distribution performs the worst compared to the others.

In the next step, the best-fit distribution was selected using the AIC criterion. The obtained AIC values (Fig. 3) for the individual pixels were averaged over the catchment area. The winning distribution was the one with the lowest AIC value. For the 1-, 3-, and 6-month accumulation period, the GAM distribution was the best choice. For the 12-month time scale, the GEV was the best option.

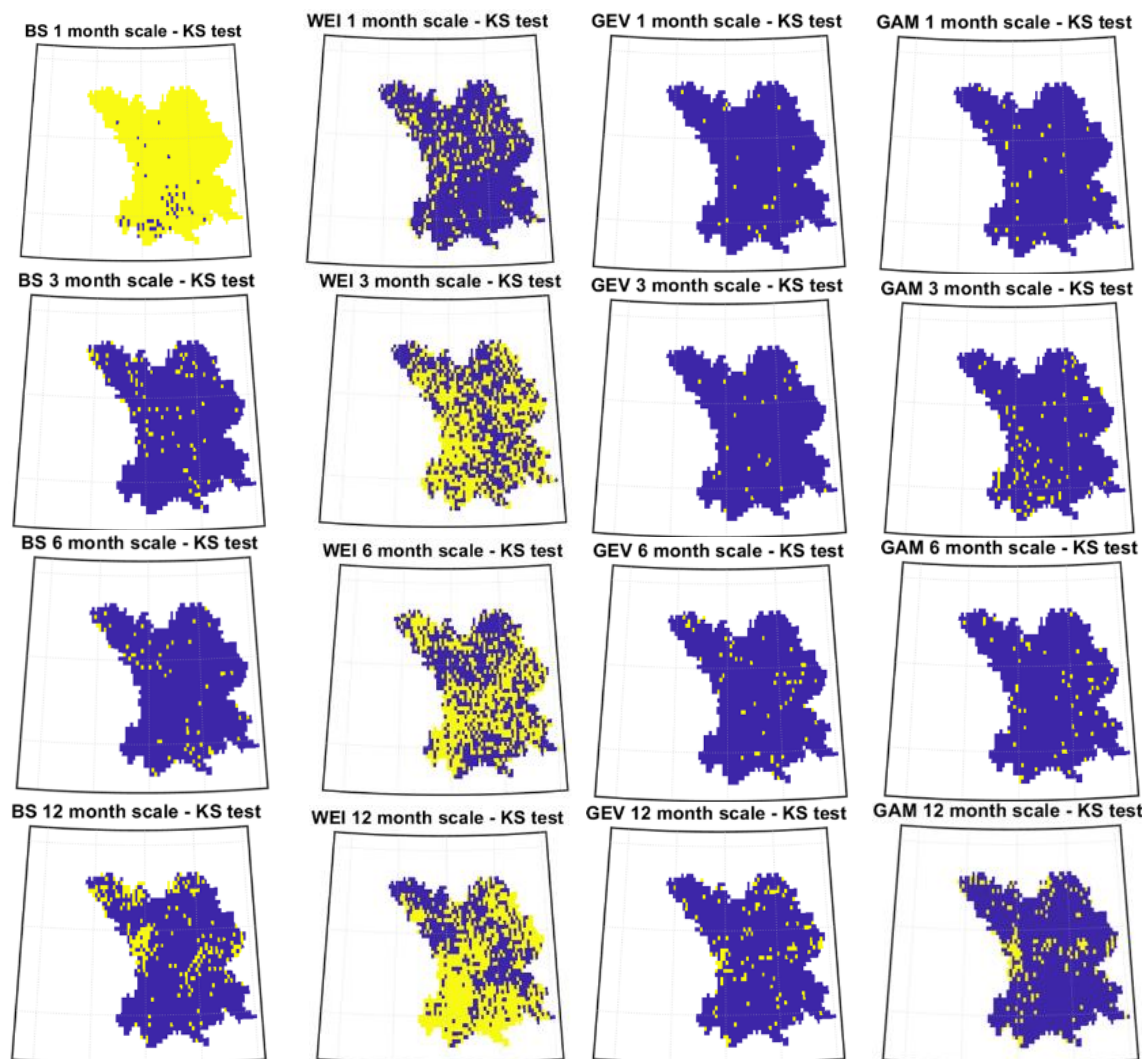


Fig. 2. Results of Kolmogorov–Smirnov test for four candidate PDFs.

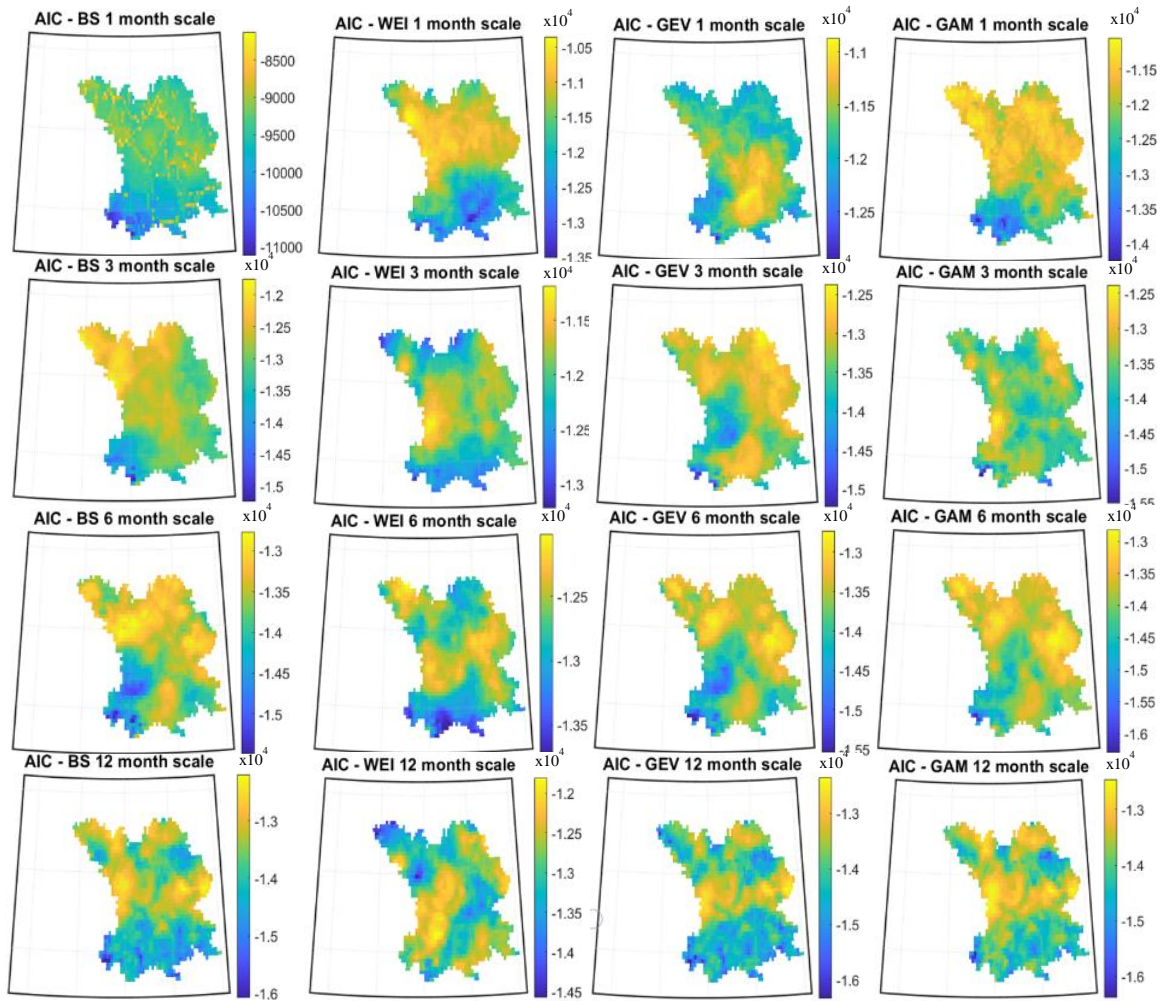


Fig. 3. Goodness-of-fit of four candidate PDFs based on AIC.

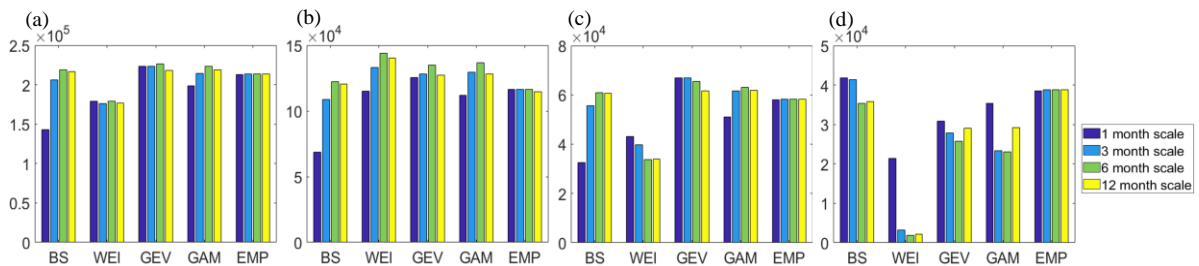


Fig. 4. Number of grid cells classified as: (a) drought – $SPI < 0$, (b) moderate drought – $SPI < -1$, (c) severe drought – $SPI < -1.5$, and (d) extreme drought – $SPI < -2$.

Finally, to show the quantitative differences in the area classified as a drought event, the SPI values calculated using the proposed distributions were compared (Fig. 4). Nonparametric SPI obtained using the empirical distribution function (EMP) were also presented. They were derived using the Gringorten plotting position approach (Gringorten 1963). The results were shown for different drought categories (moderate, severe, extreme) taking into account different accumulation periods. Analyzing all drought events ($SPI < 0$), it is evident that variation in their number depends on PDF type used to calculate the drought index. Significant differences can be observed for the WEI distribution for all accumulation periods compared to the other distributions. The WEI distribution tends to underestimate the number of droughts. It is particularly

noticeable for the severe and extreme drought categories (Fig. 1c,d.). For all drought events, the BS distribution underestimates the number of droughts for a 1-month accumulation period. The same regularity is obtained for moderate and severe droughts. The BS distribution stands out in respect to extreme droughts, clearly overestimating the number of droughts (Fig. 1d) compared to other theoretical distributions (especially for the 1- and 3-month accumulation period). Comparing the results with the EMP approach, they are generally consistent to those obtained using the GAM and GEV distributions (Fig. 4a,b,c.). Significant differences occur only for extreme droughts (Fig. 4d). The EMP approach shows high stability of the results for individual accumulation periods, yielding a similar number of drought events for each accumulation period. This regularity is observed for all drought categories. Preliminary results indicate significant discrepancies in the spatial classification of individual drought categories, indicating high uncertainty in determining the area affected by severe and extreme droughts.

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